Beyond Signaling and Human Capital: Education and the Revelation of Ability

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Abstract

In traditional models of ability signaling, higher ability workers obtain more education and employers use education to statistically discriminate in setting wages. In this paper, we argue that education plays a much more direct role in the labor market. Using data from the NLSY, we provide evidence that college allows individuals to directly reveal their ability to potential employers. Our results suggest that ability is observed nearly perfectly for college graduates but is revealed to the labor market more gradually for high school graduates. Consistent with the notion that ability is directly revealed in college market, we do not find any racial differences in wages or in returns to ability for college graduates. By contrast, blacks earn 6-10 percent less than whites of comparable ability in the high school market, a difference that might arise as a result of statistical discrimination. That a wage penalty exists for blacks in the high school but not the college labor market also helps to explain why, conditional on ability, blacks are more likely to earn a college degree.

1 Introduction

In traditional models of ability signaling [Spence 1973, Weiss 1995], education provides a way for individuals to sort into groups (education levels) that are correlated with ability. Employers then use education to statistically discriminate, paying wages that depend in part on the average ability of the individuals with the same level of education. Building on these models, Farber and Gibbons (1996) and Altonji and Pierret (2001) develop a framework in which employers do not initially observe the ability of a worker but learn about it over time. As employers gather more information about the ability of a worker, they rely less on education and more on the new information in determining the wages. In these dynamic learning models, education serves as a tool for workers to signal their unobserved ability, although its role in determining wages decreases with experience.

In this paper, we argue that education plays a much more direct role in the labor market. Specifically, we provide evidence that college allows individuals to directly reveal key aspects of their ability to potential employers[1]. Using data from the NLSY, we show that the returns to AFQT, our measure of ability, are large for college graduates immediately upon entering the labor market and do not change with labor market experience. In contrast, returns to AFQT for high school graduates are initially very close to zero and then rise steeply with experience. Completely analogous experience profiles also hold for the return to father's education. These results suggest that key aspects of ability are observed perfectly for college graduates but are revealed to the labor market more gradually for high school graduates.

There are a number of potential factors that likely contribute to ability revelation in the college labor market. Resumes of recent college graduates typically include information on grades, majors, standardized test scores and, perhaps even more importantly, the college from which the individual graduated[2]. In this way, our analysis certainly leaves open the possibility that sorting of individuals across colleges may play a significant role in the revelation of ability in the college market. It does, however, imply a more limited role of educational attainment per se in signaling ability in the college market[3].

The insight that ability is revealed in the college labor market but not in the high school market has a great deal of power in explaining racial wage differences. In the college market, consistent with the notion that ability is perfectly revealed, we find no differences in wages or the

[1] The main analysis presented in the paper limits the sample to males. Conducting a similar analysis for females is slightly more complicated due to greater concerns about selection into the labor market. Preliminary results for females that use the procedure outlined in Neal (2004) to deal with selection reveal remarkably similar patterns to those for males.

[2] In the analysis presented below, we demonstrate that this type of information explains a large portion of the variation in AFQT scores and father's education.

[3] This has important consequences for the large empirical literature that examines the extent to which the college wage premium is due to productivity enhancement versus ability sorting. See, for example, Fang (2006), Altonji and Pierret (1998), Lange (2007), Ashenfelter and Krueger (1994), Weiss (1995), Lang (1994), Stiglitz (1975), Mincer (1974) and Becker (1964). Our analysis also naturally suggests a reinterpretation of the findings of the employer learning literature following Altonji and Pierret (2001).

returns to ability across race[4]. The lack of evidence of statistical discrimination in the college market is especially noteworthy given the large difference in the AFQT distribution for college-educated blacks and whites[5]. By contrast, we estimate that blacks earn 6-10 percent less than whites with the same AFQT scores in the high school labor market. Such a wage difference would arise naturally if employers use race to statistically discriminate given the apparent difficulty in inferring ability upon entry into the high school market.

These results related to racial wage differences also provide a coherent explanation for the fact that, conditional on education, blacks obtain more education than whites (Lang and Manove (2006)). Facing a wage penalty in the high school labor market (possibly due to statistical discrimination) but not in the college labor market, blacks clearly have more incentive to obtain a college degree than whites with comparable AFQT scores. Our analysis also rules out other potential explanations for the greater level of educational attainment of blacks. One such explanation that has been put forth in the literature is that employers have more difficulty assessing the ability of blacks versus whites[6]. In fact, we find no difference in the initial level or speed of employer learning for blacks and whites in both the high school and college labor markets.

The immediate conclusions from our analysis imply that (college) education plays a significant role in directly revealing ability and that this mechanism provides a coherent explanation the observed racial differences in both wages and educational attainment. More generally, our analysis suggests that our understanding of the role of education in the labor market needs to move beyond the traditional dichotomy between human capital formation and signaling towards a more nuanced understanding of the role of education in revealing ability.

The rest of the paper is organized as follows. Section 2 gives a general overview of the data we use for our empirical analysis. Section 3 presents our main empirical findings, which consist of a series of wage regressions. To fully interpret these findings, Section 4 uses the resulting coefficients to calibrate a simple model of employer learning and statistical discrimination. Section 5 presents some additional specifications of our main estimating equations and Section 6 concludes.

[4] If anything, blacks with especially high AFQT scores appear to earn a premium upon graduating from college.

[5] The mean AFQT for blacks is approximately one standard deviation lower than that of whites in both the high school and college samples.

[6] This is a key potential explanation explored in Lang and Manove (2006). Using a different argument, they also reject this explanation. More generally, asymmetric employer learning due to race and differences between incumbent and outside firms is explored in work of Schonberg (2007), Pinkston (2006), Zhang (2006), DeVaro and Waldman (2004), Bernhardt (1995), Gibbons and Katz (1991), Greenwald (1986), Waldman (1984).

2 Data

The data used in this study come from the 1979-2004 waves taken from NLSY79. The sample selection in this paper follows as closely as possible the criteria used in Altonji and Pierret (2001) and Lange (2007). Our main analysis is restricted to white or black men who have completed 12 years or 16 years of education, i.e. who have exactly a high school or a college degree. We consider a respondent to have entered the labor market the moment that s/he reports to have left school for the first time. Actual experience is the weeks worked divided by 50 and potential experience is defined as the years since the respondent first left school. This way of constructing potential experience, as in Lange (2007), captures the time spent in the labor market better than age minus education seven as in AP. If the respondent leaves the labor market and goes back to school, we subtract the added years of schooling from the experience measures. Military jobs, jobs at home or jobs without pay are excluded from the construction of experience and from the analysis.

The wage variable is the hourly rate of pay at the most recent job from the CPS section of the NSLY. The real wage is created using deflators from the 2006 report of the president. We limit real wages to more than one dollar and less than one hundred dollars per hour. In order to make it comparable across individuals, we standardize the AFQT score by age when test was taken to have a mean zero and standard deviation one. We use data from the main and the supplementary sample of the NLSY79, and this means that blacks and disadvantaged whites are oversampled. All of the statistics in this study are unweighted. A more detailed explanation of the sample creation is given in the data appendix.

Table 1 summarizes the main variables in our sample. Worth noting from Table 1 are the differences in AFQT scores for blacks and whites of the same education level. For both college and high school graduates, this gap extends to about one standard deviation of the AFQT population distribution. This result is consistent with the finding by Lang and Manove (2006) that, conditional on the AFQT, blacks tend to get more education than whites. Also it is clear from the table that conditional on age, blacks tend to earn lower wages and accumulate less labor market experience than whites. These distinct wage and experience profiles could arise because of labor market discrimination, racial differences in AFQT scores or ability in general, or a combination of both. Finally, there are racial differences in residential location; Blacks reside disproportionately in the South and in urban areas.

Table 1: Summary Statistics for College and High School Graduates by Race

	Blacks			Whites		
	Total	HS Grad	Col Grad	Total	HS Grad	Col Grad
Observations	7,177	6,122	1,055	16,548	12,049	4,499
AFQT						
Mean	-.6638	-.8400	.3586	.4832	.2522	1.1019
Std. Dev.	.8778	.7694	.7624	.8059	.7853	.4600
Urban Residence (%)	83.38	81.82	92.48	72.60	68.71	83.02
Region (%)						
Northeast	14.77	15.21	12.23	21.34	20.18	24.45
North Central	15.68	14.79	20.85	35.59	36.68	32.68
South	62.51	63.99	53.93	28.37	28.13	28.99
West	7.04	6.01	12.99	14.70	15.01	13.88
Log of Real Wage						
Ages <25	6.4747	6.4529	6.8439	6.6077	6.5786	6.8334
Ages 25-30	6.6494	6.575	7.0168	6.8842	6.7955	7.0704
Ages 30-35	6.7055	6.6135	7.1250	7.0235	6.9056	7.2564
Ages >35	6.7954	6.7099	7.2334	7.1298	6.9753	7.4524
Actual Experience						
Cum. Weeks Worked/52						
Ages <25	2.4014	2.4441	1.6588	2.7329	2.8576	1.8007
Ages 25-30	5.5039	5.7230	4.4587	5.9620	6.5827	4.7134
Ages 30-35	8.7102	8.6782	8.8555	9.5554	9.7035	9.2667
Ages >35	12.151	11.987	12.9811	13.5336	13.2082	14.2011
Cum. hours worked/52						
Ages <25	2.3447	2.3991	1.4916	2.7531	2.9371	1.5381
Ages 25-30	5.9829	6.3290	4.5113	6.7856	7.9617	4.8009
Ages 30-35	10.161	10.323	9.5240	11.7873	12.8837	10.0964
Ages >35	15.015	15.062	14.8135	17.0946	17.8767	15.8182
Potential Experience						
Years Since Left School						
Ages <25	3.3615	3.4491	1.7402	3.2930	3.5116	1.5442
Ages 25-30	7.6618	8.2728	4.6695	7.1585	8.3951	4.5627
Ages 30-35	12.363	12.9483	9.6907	11.8856	13.1961	9.2956
Ages >35	17.430	18.0154	14.435	17.0440	18.2257	14.5765

3 Baseline Results

Given limited information, employers have incentives to rely on easily observed characteristics such as education and race to assess the productivity of a potential worker. In pure signaling models of education [Spence 1973, Weiss 1995] education serves as a (costly) mechanism for workers to sort on ability. Employers then use the average group ability of the education level the worker belongs to determine wages. In many cases race can also be a predictor of ability, so employers may engage in the illegal act of using race to determine wages.

The employer learning literature argues that if AFQT is not directly observable by firms, it will have a limited relationship to initial wages. As workers spend more time in the labor market, employers become better informed about their ability, leading to an increased correlation between wages and AFQT with experience. As employers learn directly about ability, they need to rely less on correlates of ability and, therefore, the returns to education decline over time. These predictions have been shown to hold in Altonji and Pierret (2001) (AP thereafter) and Farber and Gibbons (1996). We replicate the main results of AP using our sample and present results in the appendix.

In this paper we argue that education is more than a tool for workers to signal their ability. Our hypothesis is that although employers learn slowly about the ability of high school graduates, graduation from college directly reveals the ability of workers. If our hypothesis is true, pooling all education levels in wage regressions can lead to biases and misinterpretation of the results. Examples of papers that pool all the education levels and analyze employer learning and statistical discrimination include AP, Bauer and Haisken-DeNew (2001), Farber and Gibbons (1996), Galindo-Rueda (2003) and Lange (2007). We test our hypothesis and analyze racial differences in wages and returns to ability by splitting the sample into college and high school graduates. We formulate a simple econometric model similar to that of AP, and estimate it separately for each of the two education levels. For each group the log wages equation is:

$$\begin{aligned} w_i &= \beta_0 + \beta_2 r_i + \beta_{AFQT} AFQT_i + \beta_{r,x}(r_i \times x_i) + \beta_{AFQT,x}(AFQT_i \times x_i) \\ &\quad + \beta_{r,AFQT}(r_i \times AFQT_i) + \beta_{r,AFQT,x}(r_i \times AFQT_i \times x_i) + f(x_i) + \beta'_\Phi \Phi_i + \varepsilon_i \qquad (1) \end{aligned}$$

Log wages w_i of individual i are given as a linear interacted function of race r_i, AFQT, experience x_i, and other controls Φ_i.

We restrict the sample to potential experience levels less than thirteen for the high school sample, and less than ten for the college sample. The reason for this, as explained in the appendix that replicates AP, is that there exist a nonlinear relation between log wages, AFQT and potential experience. In order to keep the interpretation of the coefficients simple, we focus on the approximately linear region of this relation. This region seems to correspond to experience levels less than thirteen and less than ten for the high school and the college sample respectively. We also exclude from our analysis observations that correspond to the same year that individuals responded that they left school. There were not many such observations, and they were dropped because they were very noisy and are reported during the transition period to the job market. In all of our specifications we control for urban residence and for year fixed effects. We also report White-Huber standard errors that take into account correlation at the individual level over time[7].

3.1 Education and learning

Following the interpretation of AP, if employers do not initially observe ability but learn about it over time, the weight placed on AFQT initially should be small and it should increase with experience. This means that the coefficient β_{AFQT} should be close to zero, and $\beta_{AFQT,x}$ should be positive and sizable. On the other hand, if employers directly observe AFQT, the returns to AFQT should be high initially and should not change much over time. This case translates to a sizable coefficient β_{AFQT} and a relatively small $\beta_{AFQT,x}$. We estimate equation (1) separately for high school and for college graduates and present the results in Table 2. Because we are working with log wages, β_{AFQT} is the percent change in real wages as a response to an increase of AFQT by one standard deviation. We divide the interaction of any variable with experience by ten so the coefficient $\beta_{AFQT,x}$ is the change in the wage slope between the periods when $x = 0$ and $x = 10$.

Specification (1) in Table 2 estimates equation (1) by setting $\beta_{r,AFQT}$ and $\beta_{r,AFQT,x}$ to zero. This is the equivalent specification of AP for our HS sample. The coefficient on AFQT is .0060 (.0130) and statistically insignificant, which suggests that initially there are no returns to AFQT. This is consistent with the view that AFQT is not readily observable to employers when they make wage setting decisions.

Also, consistent with the employer learning literature the coefficient on AFQT$\times$exper/10 is

[7] In additional specifications not reported in the paper we added a complete set of year-education and year-afqt interactions. Adding these additional controls had no effect on the qualitative nature or statistical significance of the key results presented below.

.1265 (.0176) and statistically significant at the 95% level. This means that after ten years in the market, wages will increase by about 13% as a response to an increase of AFQT by one standard deviation. The results do not change under specification (2), which includes additional controls for region of residence and part time jobs. Consistent with the employer learning literature, for the high school sample the returns to AFQT are initially zero but increase sharply over time.

It is worth pointing out that there is another potential explanation for the AFQT-experience profile revealed in specifications (1) and (2) of Table 2. In particular, the observed profile may simply reflect the actual impact of AFQT on the productivity of high school graduates as they gain experience in the labor market. Perhaps AFQT simply does not matter for the entry-level jobs performed by high school graduates but matters more as workers gain experience. We take up this issue formally in Section 4 below, where we develop a model of employer learning and statistical discrimination that uses the regression coefficients reported here to separately identify the speed of employer learning and the true productivity of AFQT at different experience levels. That analysis supports the conclusion that employers initially observe a very noisy measure of ability and that it takes a considerable amount of time for an individual's true productivity to be revealed in the high school labor market.

Specifications (3) and (4) of Table 2 repeat the same empirical exercise for the college market revealing a very different experience profile for the returns to AFQT. In specification (3), the coefficient on AFQT enters with a magnitude of .1467 (.0364) and it is statistically significant at the 95% level. The coefficient on the interaction AFQT$\times$exper/10 is not statistically significant with a rather small magnitude of .0179 (.0611). In contrast to the high school sample, there are substantial returns to AFQT upon entry into the labor market (about a 15 percent increase in real wage for a standard deviation increase in AFQT). Moreover, the returns to AFQT do not increase much with experience, rising to only 16-17 percent after ten years of labor market experience. This AFQT-experience profile suggests that employers essentially observe AFQT perfectly at the time of initial entry into the college labor market and learn very little with experience[8].

There are a number of potential factors that likely contribute to ability revelation in the college labor market. Resumes of recent college graduates typically include information on grades, majors, standardized test scores and, perhaps even more importantly, the college from

[8]While AFQT represents only a single dimension of ability, in Section 5 below, we report results that reveal a remarkably similar pattern for father's education

Table 2: The Effects of AFQT on Log Wages for High School and College Graduates

	High School		College	
	(1)	(2)	(3)	(4)
Model:				
Black	-.0628*	-.0483	.0922	.0867
	(.0267)	(.0259)	(.0575)	(.0563)
Standardized AFQT	.0060	.0078	.1467**	.1403**
	(.0130)	(.0129)	(.0364)	(.0369)
AFQT x experience/10	.1265**	.1187**	.0179	.0281
	(.0176)	(.0173)	(.0611)	(.0608)
Black x experience/10	-.0369	-.0398	-.0823	-.0681
	(.0350)	(.0345)	(.0959)	(.0961)
R^2	0.1628	0.1871	0.1553	0.1688
Additional variables	No	Yes	No	Yes
No. Observations	11798	11775	3373	3373
Experience measure: Years since left school for the first time				

Note - Specifications (1) and (3) control for urban residence, a cubic in experience and year effects. Specifications (2) and (4) also control for region of residence and for part time vs full time jobs. Potential experience is restricted to less than thirteen and ten years for the high school and the college market.The White/Huber standard errors in parenthesis control for correlation at the individual level.

* statistical significance at the 95% level

** statistical significance at the 99% level which the individual graduated. In the appendix we show how going to college may reveal AFQT by regressing AFQT on SAT, PSAT, ACT and college major. As it can be seen in Table 8, the R^2 of these regressions is rather high ranging from 0.5674 to 0.7325 depending on the specification. This shows that college major and standardized test scores have a lot of predicting power with respect to AFQT. A more detailed discussion of these regressions can be found in the appendix.

3.2 Racial Differences

3.2.1 Racial differences in wage profiles

There are significant differences in the average AFQT of whites and blacks in both the high school and college samples. As shown in figure 1, the mean and the median of the black distribution lie about one standard deviation below the white distribution for both high school and college graduates. As a result, if employers do not directly observe ability, they have a strong economic incentive to statistically discriminate on the basis of race.

Given the results for employer learning discussed in the previous subsection, we would expect the incentives for statistical discrimination to be strong in the high school market, where ability is initially unobserved. This is reflected in the results presented in Table 2. In particular, in specification (1) the coefficient on Black is -.0628 (.0267) and the coefficient on Black $\times$ exper/10 is -.0369 (.0350). These results imply that blacks earn wages hat are about 6 percent lower than those received by whites with the same AFQT score at the time of initial entry into the labor market. Moreover, this gap increases (insignificantly) with labor market experience so that the estimated racial wage gap at ten years of experience, conditional on AFQT, is 10 percent. These results are similar in specification (2) of Table 2 where we add additional controls[9].

Conversely, given the results for employer learning, we would expect the incentives for sta-

[9] That the racial wage gap in the high school market increases with experience is inconsistent with standard models of employer learning and statistical discrimination (see, for example, Altonji and Pierret (2001)). These models would predict that employers should weight race less as they learn more directly about worker productivity. In the next section we formulate and estimate a model of employer learning and statistical discrimination that can accommodate an increasing racial wage gap. Our model differs from the existing models as it allows for the true productivity of AFQT to change with experience. We decompose the coefficients on *Black* and AFQT into the part that comes from employer learning, and the part that comes from the true productivity of AFQT increasing over time. We find that AFQT becomes more important for productivity over time, and this generates increasingly stronger incentives for employers to statistically discriminate. If employers illegally decide to statistically discriminate, the racial wage gap may indeed widen with experience.

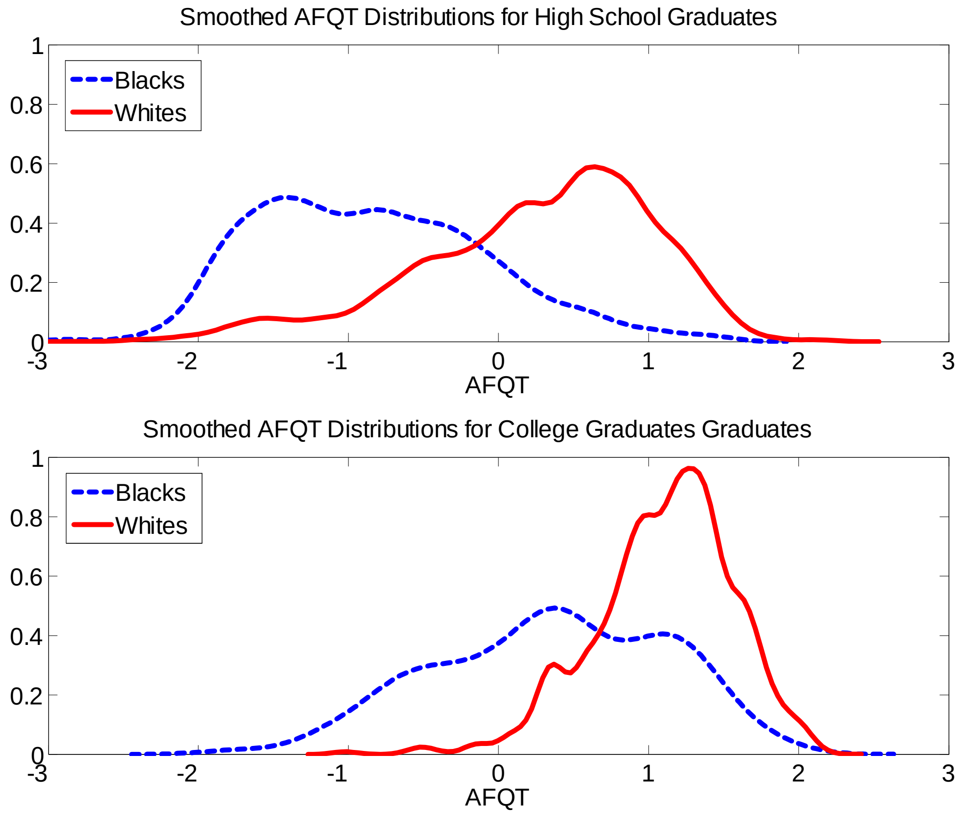

Figure 1: AFQT Distributions by Race and Education

tistical discrimination to be weak in the college market as ability appears to be more or less perfectly observed at the time of entry into the market. Specification (3) in Table 2 shows that the coefficient on Black is .0922 (.0575). This initial premium seems to dissipate after about 11 years since the coefficient on Black $\times$ exper/10 is -.0823 (.0959). Neither of these coefficients is statistically significant. The fact that blacks earn wages that are 9% higher than whites is not consistent with statistical discrimination as college graduate blacks have lower AFQT scores than whites.

The estimated wage premium for college-educated blacks may seem puzzling, and further analysis shows that it is driven by the wages of blacks with especially high AFQT scores. Table 3 shows that the premium in specification (1) does in fact decline to zero when blacks in the top ten percent of the AFQT distribution are dropped from the sample in specifications (3). The coefficient on Black is now .0238 (.0550) and that on Black $\times$ exper/10 is -.0045 (.0980), both of these are statistically and economically insignificant.

Table 3: Explaining the Black College Premium in Wages

	Full College Sample		Limited College Sample	
	(1)	(2)	(3)	(4)
Model:				
Black	.0922	.0867	.0238	.0115
	(.0575)	(.0563)	(.0550)	(.0540)
Standardized AFQT	.1467**	.1403**	.1148**	.1041**
	(.0364)	(.0369)	(.0364)	(.0370)
AFQT x experience/10	.0179	.0281	.0554	.0721
	(.0611)	(.0608)	(.0628)	(.0625)
Black x experience/10	-.0823	-.0681	-.0045	.0223
	(.0959)	(.0961)	(.0980)	(.0987)
R^2	0.1553	0.1688	0.1560	0.1689
Additional Variables	No	Yes	No	Yes
No. Observations	3373	3373	3318	3318
Experience measure: Years since left school for the first time < 10				

Note - Specifications (1) and (2) use the full college sample, while specifications (3) and (4) exclude blacks at the top ten percent of the AFQT distribution. Specifications (1) and (3) control for urban residence, a cubic in experience and year effects. Specifications (2) and (4) also control for region of residence and for part time vs full time jobs. Potential experience is restricted to less than thirteen and ten years for the high school and the college market. The White/Huber standard errors in parenthesis control for correlation at the individual level.

* statistical significance at the 95% level

** statistical significance at the 99% level

The results reported in Tables 3 strongly suggest that statistical discrimination is not present in the college market. This fits perfectly with the notion that college reveals ability. The lack of statistical discriminate in the college market is especially remarkable given the sizable differences in the distributions of AFQT between whites and blacks.

Table 4: Racial Differences in the Effect of AFQT on Log Wages

	High School		College	
	(1)	(2)	(3)	(4)
Model:				
Black	-.0600*	-.0457	.0169	.0115
	(.0294)	(.0277)	(.1108)	(.0681)
Standardized AFQT	.0046	.0065	.1115*	.1040*
	(.0158)	(.0158)	(.0451)	(.0453)
Black x AFQT	-.0054	-.0052	.0143	-.0000
	(.0272)	(.0258)	(.0732)	(.0727)
AFQT x experience/10	.1246**	.1169**	.0633	.0743
	(.0217)	(.0213)	(.0766)	(.0762)
Black x experience/10	-.0335	-.0380	.0093	.0259
	(.0385)	(.0370)	(.1161)	(.1163)
Black x AFQT x exper/10	.0048	.0045	-.0283	-.0073
	(.0372)	(.0364)	(.1277)	(.1287)
R^2	0.1607	0.1871	0.1560	0.1690
Additional variables	No	Yes	No	Yes
No. Observations	11798	11775	3318	3318
Experience measure: Years since left school for the first time				

Note - Specifications (1) and (3) control for urban residence, a cubic in experience and year effects. Specifications (2) and (4) also control for region of residence and for part time vs full time jobs. Potential experience is restricted to less than thirteen and ten years for the high school and the college market. The White/Huber standard errors in parenthesis control for correlation at the individual level.

* statistical significance at the 95% level

** statistical significance at the 99% level

3.2.2 Differences in Return to AFQT

Tables 4 report the results of specifications that include interactions of race and AFQT. These specifications allow us to examine whether the initial level and speed of employer learning differs for blacks and whites in the high school and college samples.

For the high school sample, the coefficient on Black×AFQT is -.0054 (.0272), while the coefficient on Black×AFQT× exper/10 is .0048 (.0372). Both estimates are statistically and economically insignificant implying that the process of employer learning is roughly the same for blacks and whites.

As reported in specifications (3) and (4) of Table 4, when blacks in the top ten percent of the black AFQT distribution are dropped from the sample, the coefficients on the terms that interact race with AFQT are essentially zero. In particular, in specification (3) the coefficient on Black$\times$ AFQT is .0143 (.0732) and the coefficient on Black$\times$AFQT$\times$exper/10 is -.0283 (.1277). These coefficients are even closer to zero in specification (4) where the coefficient on Black$\times$AFQT is now -.0000 (.0727), and that on Black$\times$AFQT$\times$exper/10 is -.0073 (.1287). Taken together, these results lead to the strong conclusion that, except for the high end of the AFQT distribution where college educated blacks seem to enjoy a sizable albeit statistically insignificant premium, there are no significant difference in returns to AFQT between whites and blacks in either the high school or college samples.

3.3 Explaining racial differences in education attainment

Lang and Manove (2006) (LM, hereafter) report that, conditional on AFQT, blacks obtain more education than whites[10]. Having documented this key empirical fact, LM attempt to explain it[11]. They develop a model in which employers generally observe a noisier signal for blacks than whites but this racial difference in precision declines with education. This mechanism certainly provides an increased incentive for blacks to earn more education but should also imply that, conditional only on AFQT, blacks should earn more than whites[12].

The view of the labor market suggested by our main findings provides a related and more direct explanation for why blacks obtain more education than whites with the same AFQT score. Facing statistical discrimination in the high school labor market (where ability is initially unobserved) blacks have a greater incentive to enter the college labor market thereby revealing their AFQT. Thus, under our view of the labor market, education symmetrically improves the

[10] A similar result can be seen for our sample in Figure 1, which reports the AFQT distributions for blacks and whites in both high school and college. This fact has important implications for how one thinks about racial wage differences, implying, for example, that estimating the black-white wage gap both properly requires one to control for both AFQT and education.

[11] LM first rule out differences in school quality as a potential explanation. They reason that because blacks generally attend lower quality schools they may require more education in order to reach a given level of cognitive ability. They conclude, however, that school quality differences while present cannot possibly explain the observed racial differences in educational attainment.

[12] Neal and Johnson (1996) shows that, conditional on only AFQT, the racial wage gap is smaller but blacks continue to earn less than otherwise identical whites.

precision of the signals that employers get for blacks and whites but because the value of that increased precision is greater for blacks, they obtain more education.

Our explanation is also consistent with the fact that, conditional on only AFQT, blacks earn lower wages than whites on average. In the college labor market, our results suggest that blacks earn the same as whites with identical AFQT scores, while in the high school labor market blacks at least initially earn 6 percent less than identical whites regardless of their AFQT score. While these racial differences in wages for the college and high school market do not ensure that blacks earn less than whites conditional on AFQT, they certainly allow for that possibility.

4 A Simple Model of Statistical Discrimination

Racial wage gaps have long attracted interest in the literature. Neal and Johnson (1996) showed that conditional on only AFQT the wage gap between blacks and whites is about 7 percent. Therefore they attribute most of the racial wage gap to pre-market factors that determine the AFQT. On the other hand, LM show that controlling for AFQT and education restores a racial wage gap of 15 percent. More directly related to our specifications, AP report that, after controlling for education, AFQT and their interactions with experience, blacks start off with wages at about six percent lower than whites, and this gap widens with experience. They interpret these results as lack of evidence for statistical discrimination on the basis of race, since in their view models of statistical discrimination predict that the racial wage gap should shrink. In the previous section we found similar empirical

results to AP for our high school sample. The analysis in this section will focus on explaining the increasing racial wage gap for high school graduates.

We argue that our results for the high school sample can certainly be consistent with statistical discrimination on the basis of race. One scenario that rationalizes an increasing racial wage gap under the existence of statistical discrimination is the case when the true returns to AFQT increase with experience. This is motivated by the intuition that AFQT should be more important for jobs further down the career path rather than for initial jobs right after school, since the nature of these jobs is very different. Under this scenario, blacks would be paid less initially since employers do not observe ability and put weight on average group productivity. Because the true productivity of AFQT is increasing with time, employers will have stronger and stronger incentives to statistically discriminate. Consequently, even though employers might be learning about the productivity of their workers, they might still increase the weight they put on race because of their increasing incentives to statistically discriminate.

In this section we present a model of statistical discrimination that incorporates the insights mentioned above. This model is estimated using the high school sample where employer learning seems to be present. Much of this model is based on the standard employer learning model formalized by Farber and Gibbons (1996). A model structural model of learning closely related to ours was formulated by Lange (2007). Lange estimates the speed of employer learning assuming symmetrical learning and a competitive labor market. We maintain these crucial assumptions in our specification. The more problematic assumption is assuming that employers do not have any private information about their workers. Although this assumption is still an open question in the literature, Schoenberg (2007) provides evidence that learning appears to be symmetric for the high school sample.

Our model will differ from existing models in that we allow for the true productivity of AFQT to vary over time for reasons given above. The productivity of AFQT could change also for reasons that are not captured by the model. For example if AFQT is positively correlated with cumulative training, the effect of the extra training on productivity will be captured by the parameter of true productivity of AFQT.

The goal of this section of the paper is benchmark the implications for the speed of employer learning and the true returns to AFQT with experience if the observed racial wage differences were driven entirely by statistical discrimination. Assuming that racial wage differences are driven entirely by statistical discrimination obviously rules out taste-based discrimination and other potential explanations for the wage gap. In discussing the results below, we describe how they would change if the wage gap was partially due to these other factors.

4.1 The setup of the model

We specify the true log-productivity of a worker as:

$$\chi_{i,x} = f(s_i) + \lambda_x(z_i + \eta_i + q_i) + \tilde{H}(x) \tag{2}$$

The function $f(s_i)$ captures the effect of schooling on productivity for individual i. The variable q_i represents the information about the ability of the worker that is observed by the employers, but that is not available to the researcher. On the other hand, z_i is a measure of ability observed by the researcher but not the employers. In our case this variable is the AFQT score. The part of productivity that is not captured by neither the employer nor the researcher is given by η_i. The productivity of (z, q, η) is captured by the parameter λ_x[13]. Finally, $\tilde{H}(x)$ denotes a function of how productivity depends on experience. This function is assumed to be independent of education and ability measure z_i, since this means that employers focus on predicting productivity based on variables s_i, q_i and signals they get from employers over time.

The first important assumption we make is that $z_i \perp \eta_i, q_i$.This means that the unobserved part of ability and the information that employers have initially cannot be used to predict z_i.The assumption that $z_i \perp \eta_i$ is innocuous, and there is some evidence that $z_i \perp q_i$ in the data. In all the specifications of Table 2 and Table 4 the coefficient on AFQT is almost zero and not statistically significant for high school graduates. Assuming that AFQT matters for productivity initially, this can be interpreted as evidence that the information employers have initially cannot be used to predict AFQT. We suppress the subscript i for ease of notation from now on.

Also assume (z, s, q, η) are jointly normally distributed. This means that we can means that the expectation of η given (s, q) is linear in (s, q):

$$\eta = \alpha_1 s + \alpha_1 q + v \tag{3}$$

We also assume that although the employers do not observe z, they observe an average $\bar{z} = E(z|s, x, race)$ of the group the worker belongs to. Specifically, in our case employers know the average AFQT for each race. Employers then predict z by the linear relation:

$$z = \bar{z} + e \tag{4}$$

Substituting equation (4) in (2) we can write the initial log-productivity at $x = 0$ as:

$$\begin{aligned} \chi &= rs + \lambda_x(\bar{z} + e + \eta + q) + \tilde{H}(x) \\ &= E(\chi|\bar{z}, q) + \lambda_0(e + \eta) \end{aligned} \tag{5}$$

So $\lambda_0(e + \eta)$ is the expectation error employers have initially. Over time, as they observe job performance and learn about χ, this expectation error decreases. More specifically, every period x employers get a signal given by:

$$y_x = z + \eta + \varepsilon_\tau \tag{6}$$

where ε_x is independently distributed over time as a normal with a time dependent variance σ_x^2. We maintain that ε_x is orthogonal to all other variables in the model.

[13] The lack of separate coefficients for z, η, q is harmless since we can define η and q such that their coefficients are the same as that of z.

Similar to Lange (2007), the normality assumptions that we have made so far make the structure of employer learning very simple. In the initial period when $x = 0$ the mean of the prior of employers' beliefs about $(z + \eta)$ is:

$$\mu_0 = \bar{z} + \alpha_1 s + \alpha_1 q \tag{7}$$

Next period when $x = 1$ the employers get a signal y_1 so they update their beliefs. Because of the normality assumption the mean of the posterior is now:

$$\mu_1 = (1 - \theta_1)\mu_0 + \theta_1 y_1 \tag{8}$$

where θ is some optimal Bayesian weight that the employers put on the prior mean.

The mean of the posterior at time x becomes the mean of the prior at time $x + 1$ when employers again update their posterior using the new information y_{x+1}.

$$\begin{aligned} \mu_{x+1} &= (1 - \theta_{x+1})\mu_x + \theta_{x+1} y_{x+1} \\ &= (1 - \theta_{x+1})\left[(1 - \theta_x)\mu_{x-1} + \theta_x y_x\right] + \theta_{x+1} y_{x+1} \end{aligned} \tag{9}$$

This process continues for any amount of experience as long as the worker's performance is observed by the employers. At time x employers would expect the productivity of a worker to be:

$$E_x(\chi|\bar{z}, q, Y^x) = rs + \lambda_x q + \lambda_x \left[(1 - \theta_x)\mu_{x-1} + \theta_x y_x\right] + \tilde{H}(x) \tag{10}$$

where $Y^x = \{y_{1,}...y_x\}$.As employers learn more and more the term $\left[(1 - \theta_x)\mu_{x-1} + \theta_x y_x\right]$ converges to $(z + \eta + q)$ so their expectation error collapses to zero.

4.2 The wage equation

Similar to the standard employer learning literature, we will maintain the assumption that all employers have access to the same information[14] and that labor markets are competitive. Wages are then set equal to the expected productivity of a worker:

$$W = E[\exp(\chi)|\bar{z}, q, s, Y^x] \tag{11}$$

The normality assumptions above imply that the distribution of χ conditional on (s, q, Y^x) is normal. Using properties of a lognormal distribution $E[\exp(\chi)|\bar{z}, q, s, Y^x] = \exp(E[\chi|\bar{z}, q, s, Y^x]+$

[14] Schoenberg (2007) reports that for white high school graduates, the sample we are working with, learning appears to be symmetric, meaning firms do not have any private information. Since we find there is no racial differences in the returns to AFQT, learning must be symmetric even for high school graduate blacks.

$\tilde{H}(x) + \frac{\sigma_x}{2}$).The expectation error is independent of $(\bar{z}, q, s, Y^x, \eta)$, so $\frac{\sigma_x}{2}$ does not vary with $(\bar{z}, q, s, \eta)$. We can then write the log-wages as:

$$w_x = \lambda_x \left[(1-\theta_x)\mu_{x-1} + \theta_x y_x\right] + C_x \tag{12}$$

where

$$C_x = rs + \lambda_x q + \tilde{H}(x) + \frac{\sigma_x}{2} \tag{13}$$

Equation (12) gives the wages paid to a worker given $(\bar{z}, q, s, Y^x)$. We cannot observe q and Y^x, so in order draw empirical conclusions we need to express log-wages as a function of what we observe or $(\bar{z}, z, s, x)$. The fist step to doing this is to define a linear projection of (q, η) :

$$\begin{aligned} q &= \gamma_1 s + u_1 & (14)\\ \eta &= \gamma_2 s + u_1 & (15)\end{aligned}$$

This allows us to determine log wages as a function of only $(\bar{z}, z, s, x)$. This linear projection is given by[15]:

$$E^*(w_x|z,s) = \lambda_x \left[(1-\theta_x)E^*(\mu_{x-1}|z,s) + \theta_x E^*(y_x|z,s)\right] + c_x \tag{16}$$

where

$$c_x = rs + \lambda_x(\gamma_1 s + u_1) + \tilde{H}(x) + \frac{\sigma_x}{2} \tag{17}$$

Substituting in eq. (16) for μ_x as given in eq. (9), and for q given in eq. (14), we can write the wages at $x = 1$ as:

$$w_1 = \lambda_1 \left[(1-\theta_1)\bar{z} + \theta_1 z\right] + k_1 \tag{18}$$

where:

$$k_1 = \lambda_1(1-\theta_1)\left[\alpha_1 s + \alpha_1(\gamma_1 s + u_1)\right] + c_1 \tag{19}$$

The log-wage of at period $x = 1$ is a weighted average of the mean group AFQT and of the AFQT score plus a constant. The constant k_1 reflects that employers prior depends not only on mean ability $\bar{z}$, but also on schooling s and information available only to employers q. For clarity we show how wage in period $x = 2$ is determined:

$$\begin{aligned} w_2 &= \lambda_2 \left\{(1-\theta_2)\left[(1-\theta_1)\bar{z} + \theta_1 z\right] + \theta_2 z\right\} + k_2 \\ &= \lambda_2 \left\{(1-\theta_2)(1-\theta_1)\bar{z} + \left[(1-\theta_2)\theta_1 + \theta_2\right] z\right\} + k_2 \\ &= \lambda_2 \left\{\prod_{i=1}^{2}(1-\theta_i)\bar{z} + \left[1 - \prod_{i=1}^{2}(1-\theta_i)\right] z\right\} + k_2 \qquad (20)\end{aligned}$$

[15] Here $E^*(X|Y)$ denotes the linear projection of X on Y.

where

$$k_1 = \lambda_2 \prod_{i=1}^{2}(1-\theta_i)\left[\alpha_1 s + \alpha_1(\gamma_1 s + u_1)\right] + c_2 \tag{21}$$

This procedure of determining the wages could be generalized so that the log-wages at experience x can be written as:

$$w_x = \lambda_x \left\{ \prod_{i=i}^{x}(1-\theta_i)\bar{z} + \left[1 - \prod_{i=i}^{x}(1-\theta_i)\right] z \right\} + k_x \tag{22}$$

where

$$k_x = \lambda_x \prod_{i=1}^{x}(1-\theta_i)\left[\alpha_1 s + \alpha_1(\gamma_1 s + u_1)\right] + c_x \tag{23}$$

In order to give the log-wage equation the form shown in Lange (2007) we can rewrite it as:

$$w_x = \lambda_x \left\{(1-\Theta_x)\bar{z} + \Theta_x z\right\} + k_x \tag{24}$$

This representation of the log-wage has an intuitive interpretation. Fist of all, for a given level of schooling, which is the case in our estimation, k_x is only a experience specific constant. In this case the wages will be a function of experience plus a weighted average of the mean group ability $\bar{z}$ and the actual ability z. The first source of the weight put on $\bar{z}$ and z comes from employers learning over time. If initially employers do not observe anything that is correlated to z, they rely on group averages $\bar{z}$ to set the wages. In this case $\Theta_x = 0$, so all the weight is put on $\bar{z}$. As employers get to observe more signals about the productivity of the worker, the weight will gradually be shifted from group mean $\bar{z}$ to actual ability z[16]. This means that as experience increases $\Theta_x \to 1$[17]. The rate of this convergence which is also the speed of learning will depend on the quality of the signals that employers get every period.

The other part of the weight put on $\bar{z}$ and z comes from the true productive value of the ability measures (z, η, q) which are correlated with $\bar{z}$ and z. This time varying true productive value is captured by parameter λ_x. As argued above, suppose workers ability measures (z, η, q) are not as important for productivity for initial jobs as they are for jobs later in the career. Therefore, λ_x will be low initially and it will increase over time, which means that additional

[16] Similarly, employers distribute some weight on education intitially, which dicreases over time as employers learn more about ability. This education profile is captured in k_x. We do not pay particular attention to this since we are interesed in statistical discrimination on the basis of race and not education.

[17] Mathematically this happens because as long as employers are getting new signals every period $\prod_{i=i}^{x}(1-\theta_i) \to 1$ as x increases since $(1-\theta_i) < 1$.

weight will be put on both $\bar{z}$ and z as time passes. Interestingly, this can cause the weight put on $\bar{z}$ to increase instead of decreasing as it would if the only weight came from learning. As long as λ_x increases faster than the speed of learning in the sense that $\lambda_x/(1-\Theta_x) > 1$, more and more weight will be put on group average ability $\bar{z}$. In our empirical application in the next section we will show that this is indeed the case.

4.3 Estimation

Equation 24 specifies the relationship between log wages, schooling and ability over the career of the worker. As mentioned above, for a given experience, log wages are a linear function of average group ability, individual ability and schooling. We are only interested in the case of high school graduates, so education is also held constant at 12. This means that we can estimate equation (24) directly by regressing log wages on mean AFQT of racial group and AFQT interacted with a full set of experience dummies as Lange (2007):

$$w_{t,x} = \sum_x \beta_{x,\overline{AFQT}_{race}} \overline{AFQT}_{race} \cdot D_x + \sum_x \beta_{x,AFQT} AFQT \cdot D_x + \beta'_\Phi \Phi_{i,t} + \beta_x D_x + \varepsilon_x \tag{25}$$

The variable D_x denotes a set of dummy variables that take the value one if experience is equal to x and zero otherwise. To capture the effects of education and of the variables that only employers observe denoted by k_x in equation (24), we include experience dummies directly in the regression so this effect will be captured by $\beta_{0,x}$.We also control for demographic controls which are denoted as $\Phi_{i,t}$.

Empirically, as can be seen in Table 1, the difference between the mean of AFQT for whites and blacks is 1.0922$\approx$ 1 for high school graduates. This means that instead of including $\overline{AFQT}_{race}$ in equation (25), we could include a dummy variable that takes value one if the worker is black and zero otherwise and still be able to estimate the parameters $\beta_{x,\overline{AFQT}_{race}}$ and $\beta_{x,AFQT}$. In this case $\beta_{x,AFQT}$ would be unchanged and $\beta_{x,\overline{AFQT}_{race}} = -\beta_{x,Black}$. We replace $\overline{AFQT}_{race}$ by dummy variable $Black$ and our estimating equation is:

$$w_{t,x} = \sum_x \beta_{x,Black} Black \cdot D_x + \sum_x \beta_{x,AFQT} AFQT \cdot D_x + \beta'_\Phi \Phi_{i,t} + \beta_x D_x + \varepsilon_x \tag{26}$$

We can now give a more structural interpretation to the coefficient on $Black$.Employers put weight on race for two reasons: the first part $(1-\Theta_x)$ is related to learning about ability, and the second part λ_x comes from the changing productivity value of this ability. The size and the sign of the coefficient on $Black$ would depend entirely on the experience profile of λ_x and Θ_x.

After estimating equation (26) we could solve for λ_x and Θ_x:

$$\lambda_x = \beta_{x,AFQT} - \beta_{x,Black} \tag{27}$$

$$\Theta_x = \frac{\beta_{x,AFQT}}{\beta_{x,AFQT} - \beta_{x,Black}} \tag{28}$$

The results from the described estimation procedure are presented in Figure 2. The first two plots display the estimated coefficients on Black and AFQT for each experience level. We smooth the way these coefficients evolve with experience by fitting a cubic in experience. After the smoothing, the initial racial difference in wages is about 6% and in increases to 10% in about 12 years. The returns to AFQT start at zero initially and increase to about .15 after 12 years of experience which translates to a 15% change in wages for a one standard deviation change in AFQT. These results are very similar to those previously shown in Table 2.

We use these smoothed experience profiles to calculate how much of the changes in the returns to race and AFQT can be attributed to employer learning, and how much to AFQT becoming more important over time. Sub-figures 2 and 3 of figure 2 plot the learning parameter Θ_x and the parameter λ_x, which captures the evolution of the productivity of AFQT over time. The learning parameter starts at zero and by 12 years increases to 0.6, which means employers reduce their expectation error by 60% in about 12 years. On the other hand, the true productivity of AFQT and other measures of ability starts at 0.07 initially and increases to about 0.25 in 12 years.

The difference between actual returns to AFQT in sub-figure 2 and true productivity of AFQT in sub-figure 4 is explained by the fact that employers do not observe AFQT and are learning about it over time. The weight employers put on AFQT because of their learning process is shown in sub-figure 6[18]. Initially they do not put any weight on AFQT since they don't observe it, and after 12 years they put a weight of 0.6. Workers do not get any return to the productivity of their AFQT initially, but 12 years out into their careers the return to AFQT increases to 60% of the true productivity of ability λ_x. This seems consistent with the model's feature that as employers learn more about the true AFQT of the worker, the returns to AFQT will converge to the true productivity of AFQT.

Sub-figure 5 plots the weight put on race to determine wages as a result of employer learning. This weight is initially -1 and by 12 years it drops to -0.4. Initially employers do not observe

[18] Subfigure 6 is the same as subfigure 3 since the weight on AFQT that comes from learning is exactly Θ_x.

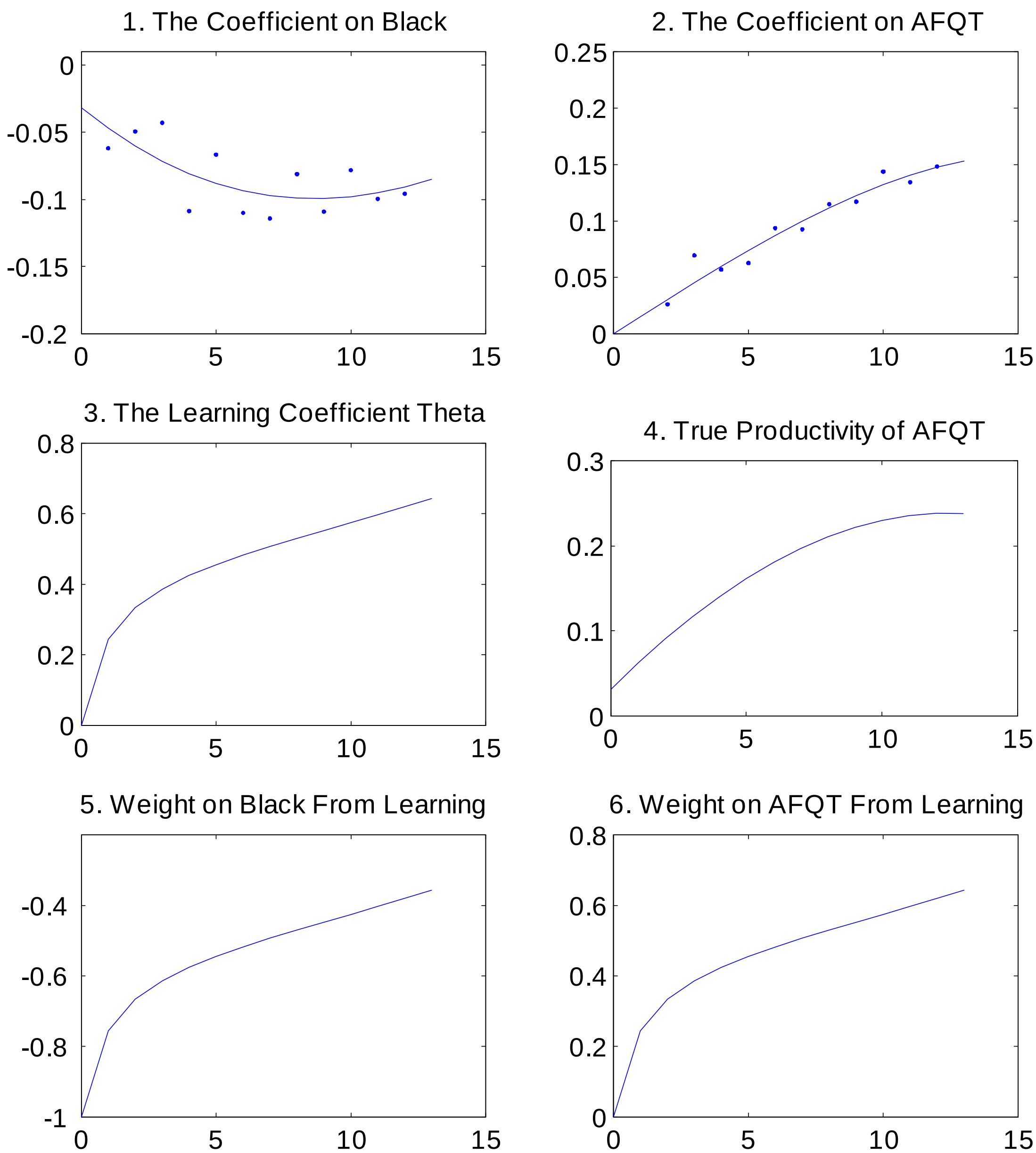

Figure 2: Plots 1 and 2 show the estimated coefficients $\beta_{x,Black}$ and $\beta_{x,AFQT}$. The estimates for $\beta_{x,AFQT}$ and $\beta_{x,Black}$ are smoothed using a cubic in experience. Plots 3 and 4 show the experience profile of the learning parameter Θ_x and the productivity parameter of AFQT λ_x. Plots 5 and 6 display the part of the weight put on Black and AFQT over experience that comes only from employer learning. This weight is $-(1-\Theta_x)$ for *Black* and Θ_x for AFQT.

ability so they have to rely heavily on the race of the worker to determine wages. As they learn over time their incentives to statistically discriminate decrease and they rely less on race and more on the observed part of AFQT. This, however, does not mean that the actual return on race should decrease with experience. Because the true returns to AFQT given by λ_x increase over time, employers have more incentives to statistically discriminate. The coefficient on race will be a result of these two opposing incentives. Our estimates show that the effect of the increasing productivity of AFQT dominates the effect of learning in determining the coefficient on race. The fact that the coefficient on Black starts negative and does not decrease with experience is therefore completely consistent with employers statistically discriminating on the basis of race and learning about ability over time.

5 Robustness Results

5.1 Controlling for Selection

All of the results presented so far do not account for selection into the labor market. Differences in labor force participation by race can be very important when estimating log wage equations as shown in Butler and Heckman (1977) and Brown (1984). In order to control for selection, we could model the decision to participate in the labor force and estimate a rich structural model of wage offers and labor market entry decisions. This, however, proves to be too complicated for the purpose of this paper. Instead we follow Neal and Johnson (1997) by assigning an arbitrary wage to non-participants and estimate a median regression for the whole sample. If the wages offers that nonparticipants receive lie below the median wage offers participants receive, these median regression allow us in a crude way to control for selection.

The results from these median regressions are presented in Table 5. All the findings presented earlier are still present in this table. Specification (1) estimates our baseline specification for the high school sample. The returns to AFQT are very small initially with a coefficient of .0174 (.0108), but increase sharply in ten years with a significant coefficient of .1407 (.0149). Blacks are paid about twelve percent less than whites and this difference increases (although insignificantly) by an additional three percent in ten years. Specification (2) allows AFQT to vary by race. We find that there are no differences in returns to AFQT since the coefficients on the interactions of AFQT with race and experience are small in magnitude and statistically significant.

Specifications (3) and (4) repeat the same procedure for the college sample. The returns

Table 5: The Effects of AFQT on Log Wages Controlling for Selection

	High School		College	
	(1)	(2)	(3)	(4)
Model:				
Black	-.1249**	-.1379**	.0611	.0343
	(.0219)	(.0540)	(.0538)	(.0662)
Standardized AFQT	.0174	.0268*	.1587**	.1413**
	(.0108)	(.0141)	(.0341)	(.0396)
Black x AFQT		-.0277		.0494
		(.0250)		(.0662)
AFQT x experience/10	.1407**	.1266**	-.0203	-.0255
	(.0149)	(.0196)	(.0624)	(.0719)
Black x experience/10	-.0313	-.0173	-.0845	-.0945
	(.0299)	(.0359)	(.0975)	(.1190)
Black x AFQT x exper/10		.0358		.0347
		(.0342)		(.1207)
Pseudo-R^2	0.0467	0.0467	0.0816	0.0825
No. Observations	13221	13221	3463	3463
Experience measure: Years since left school for the first time				

Note - In order to control for selection, we assign a zero log-wage to respondents who are not working at the time of the interview, and then estimate the log-wage equation using a median regression. Potential experience is limited to less than ten and thirteen years for the high school and the college sample respectively. All specifications control for urban residence, a cubic in experience and year effects. The standard errors reported do not control for clustering at the individual level.

* statistical significance at the 95% level

** statistical significance at the 99% level to AFQT in specification (3) are very large and significant initially with a coefficient of .1587 (.0341). These returns do not change over time since the coefficient on AFQT×exper/10 is small and insignificant with a magnitude of -.0203 (.0624). The same results can be seen in specification (4). Moreover, specification (4) shows that there are no significant racial differences in returns to AFQT. The results on racial wage differences are also unchanged since we do not find any evidence that college educated blacks are paid less than their white counterparts.

To sum up, in order to control for selection we assigned an arbitrary low wage to labor market nonparticipants, and estimated the log wage equations by median regressions. All the results from this procedure are consistent with the results we showed in previous section. We still find that employers gradually learn about the AFQT of high school graduates, but that they directly observe the AFQT of college graduates. We also find that there are no racial differences in returns to AFQT in both samples. Blacks who have a high school degree are paid less than whites, but, consistent with the view that employers directly observing AFQT, there are no racial wage differences in the college market .

5.2 Father's Education as a Measure of Ability

So far we have provided evidence that graduating from college reveals a single measure of ability AFQT. In this subsection we show that a similar pattern is found in the data for another proxy for ability that is hard to observe by employers: father's education. We estimate the log wage regressions including this new ability measure in Table 6. In all the specifications father's education is divided by ten, so the coefficients should be interpreted as the return to an increase in father's education by ten years.

Specification (1) shows that, for high school graduates, the effect of father's education on wage is initially small. This coefficient is statistically insignificant with a magnitude of .0239 (.0382). On the other hand, the interaction term F. Educ/10 × experience/10 enters significantly with a coefficient of .1632 (.0539). These two coefficients combined are consistent with the story that initially employers do not observe ability but learn about it over time. These results do not change in specification (2) where we include AFQT and its interaction with experience. Both AFQT and father's education have a small insignificant intercept and a steep and significant slope.

We now turn to specification (3), which analyses the effect of father's education on wages for college graduates. The coefficient on Father's Education/10 is still statistically insignificant, but

Table 6: The Effects of AFQT and Father's education on Log Wages

	High School		College	
	(1)	(2)	(3)	(4)
Model:				
Black	-.0530**	-.0536*	.0168	.1087*
	(.0269)	(.0305)	(.0567)	(.0596)
Father's Education/10	.0239	.0252	.0894	.0622
	(.0382)	(.0400)	(.0646)	(.0642)
Standardized AFQT		-.0004		.1328**
		(.0151)		(.0377)
Black x experience/10	-.1528**	-.0243	-.1060	-.0913
	(.0354)	(.0403)	(.0972)	(.1053)
F. Educ/10 x experience/10	.1632**	.0953*	-.0309	-.0397
	(.0539)	(.0532)	(.1123)	(.1105)
AFQT x experience/10		.1316**		.0461
		(.0203)		(.0628)
R^2	0.1327	0.1611	0.1340	0.1634
No. Observations	10077	10077	3289	3289
Experience measure: Years since left school for the first time				

Note - All specifications control for urban residence, a cubic in experience and year effects. Potential experience is limited to less than ten and thirteen years for the high school and the college sample respectively. The White/Huber standard errors in parenthesis control for correlation at the individual level.

* statistical significance at the 95% level

** statistical significance at the 99% level

its magnitude of .0894 (.0646) is quite sizable. If we compare this to the analogous coefficient in specification (1), we can see that the returns to father's education are about four times higher for college graduates than for high school graduates. The coefficient on F. Educ/10 x experience/10 enters at -.0309 (.1123) and it is insignificant. This last coefficient was very high and significant for high school graduates as it can be seen in specification (1). The same results hold even after we include AFQT, although this decreases the returns to father's education.

Although the results are statistically insignificant for college graduates, the impact of father's education on wage is very different for the college and the high school sample. The magnitudes of the coefficients show that father's education has a higher impact on wages for college graduates than for high school graduates. On the other hand, the returns to father's education significantly increase with experience for high school graduates, but for college graduates. These results combined are consistent with our main hypothesis that employers slowly learn about the ability of high school graduates, but directly observe the ability of college graduates.

6 Conclusion

The main argument in this paper is that education plays more than just a signaling role in the determination of wages. Specifically, we argue that graduation from college allows individuals to directly reveal their ability to potential employers. Using data from the NLSY, we show that the returns to AFQT, our measure of ability, are large for college graduates immediately upon entering the labor market and do not change with labor market experience. In contrast, returns to AFQT for high school graduates are initially very close to zero and rise steeply with experience. Similar patterns emerge when instead of AFQT we use father's education as a proxy for ability. These results suggest that ability is observed perfectly for college graduates but is revealed to the labor market more gradually for high school graduates.

Consistent with the notion that ability is perfectly revealed, we find no differences in wages or the returns to ability across race for our college sample. The lack of evidence of statistical discrimination in the college market is especially noteworthy given the large difference in the AFQT distribution for college-educated blacks and whites. On the other hand, we provide evidence that blacks earn six percent less than whites initially, and this gap increases with labor market experience. We argue that this wage difference arises due to statistical discrimination in the high school labor market given the information problem that potential employers face. To provide evidence for this view, we formulate and estimate a model of employer learning and statistical discrimination.

The combination of discrimination against blacks in the high school market and perfect revelation of ability in the college market is also consistent with the fact that, conditional on AFQT, blacks are more likely to earn a college degree than whites. Facing discrimination in the high school market, blacks on the college-high school margin have a stronger incentive to reveal their ability directly by attending college.

7 Appendix

A Replicating Altonji and Pierret (2001)

In this section we replicate the results reported on Altonji and Pierret (2001) using our sample selection criteria. AP estimate a log earning equation with linear interactions of education, race and AFQT with experience of the form:

$$\begin{aligned} w_i &= \beta_0 + \beta_1 s_i + \beta_2 r_i + \beta_3 z_i + \beta_{s,x}(s_i \times x_i) + \beta_{r,x}(r_i \times x_i) \\ &\quad + \beta_{z,x}(z_i \times x_i) + f(x_i) + \beta'_{\Phi}\Phi_i + \varepsilon_i \end{aligned} \tag{29}$$

Log wages w_i of individual i are given as a function of schooling s_i, race r_i, AFQT scores z_i, experience x_i, and other controls Φ_i.The results of the replication are presented in Table 7. Specification (1) uses the sample selection closest to AP with observations coming from interview years 1979-1992. The coefficients presented here slightly differ from those of AP because of few differences in sample construction. First, the construction of potential experience is slightly different. The potential experience measure here is years since first left school, and any years of additional education after entering the labor market are subtracted from the experience measure. This measure seems to capture the time a person spends in the labor market better than the experience measure in AP, which is simply age minus education minus seven. Secondly, we do not control for interactions of education and AFQT with time as that makes identification very hard and makes the estimates unstable. Regardless of the slight changes, the main qualitative results of AP are still present.

Following AP's interpretation, employers seem to statistically discriminate on the basis of education. The coefficient on education is positive and significant when a worker has no experience and falls as the worker gains more experience. On the other hand, employers initially put little weight on AFQT since it might not be visible to them. As the worker gets more experience the employers slowly learn about their ability so they increase the weight they put on AFQT. The coefficient on black is insignificant and small initially, but it becomes significant and negative over time. AP use these as evidence that there is statistical discrimination on the basis of education but not on the basis of race.

Column (2) uses the same specification for our whole sample for interview years 1979-2004. The results seem similar except for the higher intercept and flatter profile of AFQT over time. This result is not evidence of little learning in our sample as it arises because of a nonlinear

Table 7: The Effects of AFQT and Schooling on Log Wages

	(1)	(2)	(3)
Model:			
Education	.0668**	.0725**	.0831**
	(.0058)	(.0045)	(.0051)
Black	-.0008	-.0244	-.0118
	(.0227)	(.0190)	(.0207)
Standardized AFQT	.0324**	.0602**	.0310**
	(.0116)	(.0010)	(.0107)
Education x experience/10	-.0240**	-.0042	-.0259**
	(.0076)	(.0038)	(.0068)
AFQT x experience/10	.0856**	.0496**	.0954**
	(.0159)	(.0079)	(.0137)
Black x experience/10	-.0735*	-.0639**	-.0737**
	(.0299)	(.0145)	(.0251)
R^2	0.2823	0.3357	0.3044
Sample	Replication of AP Years 1979-1992	Full sample Years 1979-2004	Full sample Experience<13
No. Observations	20617	37918	25726
Experience measure: Years since left school for the first time			

Note - Specification (1) is a replication of the results of AP. We also control year effects, a cubic in experience, a cubic in time with base year 1992, urban residence, and first occupation. Regression (2) uses the whole sample for years 79-04 and doesn't control for first occupation. We see a large coefficient on AFQT initially and a flat profile. Specification (3) limits the potential experience to less than 13 so the fast increase in the AFQT coefficient over time reappears. The White/Huber standard errors in parenthesiscontrol for possible correlation at individual level.

* significance level at the 95% level

** significance level at the 99% level

relation between log wages and AFQT over experience. In order to keep the interpretation of the coefficients on AFQT simple we focus on the approximately linear part of this relation which corresponds to experience levels less than thirteen years. The regression using this criterion is presented in column (3) of Table 7. Restricting experience to less than thirteen years restores the low intercept and steep profile of AFQT. For the same reason explained above, the sample in our main analysis will be constrained to experience levels less than 13 for high school graduates and less than ten for college graduates.

B How college reveals AFQT

In order to support the idea that going to college reveals AFQT, we show that AFQT can be predicted by college major and standardized test scores. Table 8 displays the results from these regressions. Rather than the individual coefficients we are interested in the general fit of the regressions, so we focus on the R-squared. All of our specification control for major which is not shown. The R-squared in all of the specifications ranges from 0.5674 when we only control for major and PSAT scores, to 0.7325 when we control for major, SAT and PSAT scores. This result shows that employers should have a good idea of the productivity of college graduates if they can observe college major and standardized scores. Even if workers don't report standardized test scores in their resumes, employers observe the quality of the college they went to and their performance in college, which we expect are correlated with standardized test scores. Not surprisingly, the findings of Table 8 are consistent with, and support our hypothesis that going to college indeed reveals AFQT, our measure of productivity.

C Sample Creation

In this study we use the NLSY dataset for years1979-2004. We only consider observations after the respondent has left school for the first time. Actual experience is counted as the total number of weeks that the respondent declares s/he has worked since last interview after they leave school for the first time. Potential experience is constructed as time in years since the respondent left school. Valid observations are kept and even if the respondent goes back to school after leaving school for the first time but the additional years of education are subtracted from the experience measures.

Although the respondents report all the jobs held since the last interview, we only use the information of the current job they are holding at the time of the interview (CPS item). In addition, military jobs, jobs at home or jobs without pay are excluded from the construction of experience and from the analysis. The wage variable is the hourly rate of pay at the most recent job from the CPS section of the NSLY. The real wage is created using deflators from the 2006 report of the president. All observations with wages less than \$1 and more than \$100 are dropped. Our education variable is the highest grade completed by the respondent at the time of interview. The AFQT variable is normalized by age since respondents took were at different ages when they took the test.

Table 8: Predicting the AFQT for College Graduates

	(1)	(2)	(3)	(4)
Model:				
Dep. Variable: AFQT				
SAT Math Sect./10	.0234**		.0080	
	(.0037)		(.0051)	
SAT Verbal Sect/10	.0150**		.0112*	
	(.0036)		(.0052)	
PSAT Math Sect./10		.2712**	.1934**	
		(.0271)		
PSAT Verbal Sect./10		.0591*	-.0030	
		(.0288)	(.0537)	
ACT Math Sect./10				.3248**
				(.0488)
ACT Verbal Sect./10				.0345**
				(.0711)
Constant	-.7238**	-.4373**		-.2477*
	(.1432)	(.1119648)		(.1105)
R^2	0.5984	0.5674	0.7325	0.5995
No. Individuals	178	254	119	188

Note. - All the specifications above control for college major.
* significance level at the 95% level
** significance level at the 99% level

There are 5404 non-hispanic males in the NLSY79 sample. We drop 373 respondents who never left school or do not declare when they first left school. Out of remaining respondents 1489 graduated before 1978. For this group we constructed the work history before 1978 using three set of questions from the 1979 interview as in AP. Out of them, 809 respondents were dropped since their work history could not be constructed.

Next we drop 13 individuals who by the 2002 interview did not have 8 years of education, 145 if the wage was missing, 203 if AFQT was missing, and 83 individuals who at the time of the interview were not working in civilian jobs for pay or whose wages were less than \$1 or more than \$100. The final sample contains 3778 individuals and 38168 observations. After keeping only observations when the highest grade completed is 12 or 16 we are left with 2714 respondents and 23732 observations. If we were to construct the sample as AP by keeping observations before year

1993 and dropping the individuals who do not have a first occupation, the sample would contain 2968 individuals and 20753 observations (AP had 2976 individuals and 21058 observations).

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